Redefining MRI:
From Image to Insight

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Robust MRI Image Reconstruction Using a Scan-Specific Deep Learning Framework

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Magnetic resonance imaging (MRI) remains the reference modality for disease diagnosis, staging, and longitudinal assessment of treatment response across a wide spectrum of clinical conditions. To shorten acquisition, established parallel-imaging techniques—most notably Sensitivity Encoding (SENSE) and Generalized Autocalibrating Partially Parallel Acquisition (GRAPPA)—exploit the spatial information provided by multi-channel receiver coil arrays. The achievable acceleration, however, is intrinsically capped by penalties such as amplified noise, residual aliasing artifacts, and degraded signal-to-noise ratio (SNR). The consequences are tangible in neuro-oncology, where comprehensive MRI protocols frequently exceed 20 minutes even at the two- to three-fold acceleration typically delivered by GRAPPA or SENSE, posing a persistent obstacle to clinical throughput.

Deep learning has more recently reshaped the landscape of image reconstruction, mitigating several shortcomings of classical algorithms, including protracted reconstruction times and the artifacts that persist at aggressive undersampling factors. A representative example is model-based deep learning (MoDL), which couples a convolutional neural network with a parallel-imaging forward operator so that undersampled measurements can be jointly denoised and corrected. The same principle has been carried over to demanding acquisitions—for instance, the MoDL-MUSSELS variant tailored to multi-shot echo-planar imaging for diffusion MRI—recovering high-fidelity images from substantially reduced data.

A central drawback of supervised formulations is their dependence on extensive collections of high-quality ground-truth images, a requirement that is especially hard to satisfy for echo-planar acquisitions.

Self-supervised learning has emerged as a way around this bottleneck by removing the need for externally curated training data. One prominent instance is zero-shot self-supervised learning (ZS-SSL), which partitions the acquired k-space into three disjoint sets dedicated respectively to network input, loss computation, and validation. Across denoising, reconstruction, and quantitative mapping, ZS-SSL has delivered performance that matches or surpasses supervised counterparts, and its success has since inspired a growing family of self-supervised methods spanning diverse MRI applications.

This lecture presents physics-driven deep learning for image reconstruction grounded in the MoDL framework, and shows how such models can be strengthened further through self-supervised strategies in the spirit of ZS-SSL.

Keywords: *Fast MRI, Image reconstruction, Self-supervised learning, Physics-guided reconstruction*